Drones with eyes: expressive Human-Drone Interaction

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ABSTRACT

Drones are showing potential for many applications in which the interaction with humans are needed. In this paper, we demonstrate how affective computing can be applied to achieve a more natural Human-Drone Interaction. We proposed a learning approach for automatic and context-dependant coupling of emotion recognition and expression in a human-drone interaction. The drone performs facial emotion estimation to autonomously produce emotional expression through minimalistic animated eyes, using small displays. Additional testing is needed to further refine the interactions and establish how emotional interactions evolve in longer term interactions.

KEYWORDS

Human-Drone Interaction; Learning-driven behaviors; Affective Computing; Social Robotics; UAV

INTRODUCTION

Robots will increasingly become part of our lives, both in professional and social contexts. In the future, robots are expected to replace around 47 percent of total US employment by automating jobs [7], and drones will take a fair share in this process. Among all robots, drones are not a typical choice for a social partner since their applications are mostly outdoor, for example in transport and parcel delivery [8], search and rescue [2], the film industry and 3D mapping contexts [1]. We explore the potential for indoor applications of drones, in sports [17], warehouses, greenhouses, and eventually at homes. In this class of applications, the social abilities of a drone will be of higher importance for better communication and eventually for establishing long-term relations with the inhabitants of the indoor environments.

Emotion and intention are highly relevant in human-robot interactions [10]. Applying an affective dimension in human-robot interaction could reduce frustration during interaction [17], and increase robot acceptance in domestic environments [4]. One major challenge of affective interaction is to create a meaningful expression of emotion and intention in a drone with an embodiment that is hardly anthropomorphic or zoomorphic [4]. Eyes expressivity [3], and the whole body movement [4] were shown to be a very promising cue. In this study, we develop expressive drone eyes that are controlled by the emotional expression which the drone perceives from the facial expression of the interacting human. We base our assumption on the outcomes from the research on how to build longitudinal emotional interactions between people and drones on the data-driven model of emotional interactions between humans [9][11]. These results are based upon observations of 520 days long intermittent interactions between the same individuals.

RELATED WORK

Latest developments in research have already made significant steps in developing technologies that have positively affected social comfort [15] and working efficiency [14]. In attempts to recognize human emotions accurately, previous work by A. George [8] utilizes a minimal number of geometrical feature points. In this referred study, a dataset of input from a series of position numbers is reduced to only two features: eyes and eyebrows of the human face. Using only these features, an 87.4% recognition rate of facial emotions was achieved. Other related research investigates emotions in Human-Robot Interaction (HRI) [4][5][12].

Emotion or intention based interaction with drones included controlling a drone using face orientation and hand direction [12], and arm movement and body posture [18][13]. In another study, Szafir, Mutlu, and Fong [16] explored the design of a visual signaling mechanism to express a drone's intention via a ring of LED lights surrounding the drone.

We intend to explore how drones should react to the emotion of a specific person. For this purpose, the drone needs to recognize the person's emotion and change its expression automatically by controlling the openness and the direction of the drone eyes. The research and the design featured in this paper is focused on the non-verbal communication between a human and a drone, shown only through the shape of the eyes.

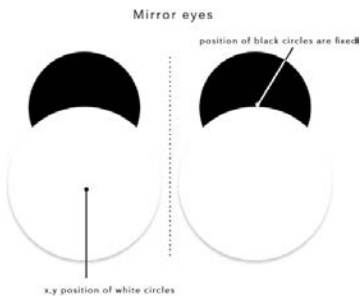

Figure 1: The expressive eyes are defined by varying two parameters of overlapping circles. This way the autonomous expression is easily achievable.

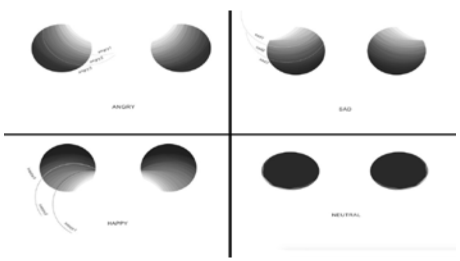

Figure 2: Visualization results of different emotional states and intensities.

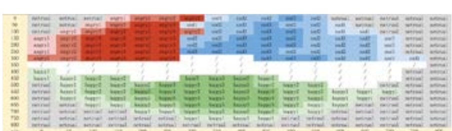

Figure 3: Emotion lookup table to find the best positions of the drone eyes.

DESIGN OF THE DRONE BEHAVIOR AND THE HUMAN-DRONE INTERACTION

Used technologies and usability testing overview

For emotion expression of the drone, simplified eyes were designed, as shown in Figure 1 and Figure 2. The eyes consist of a static black circle on a white background. A white circle with a fixed radius and a variable position is then projected on top of it, leaving a moon shaped black form. The white circle is mirrored on the opposite black eye, thus requiring only two variables to generate the both eyes (see Figure 1). Depending on the location of the white circle, the black circles will represent eyes with different emotional expressions. For this study, we limit the expressions to four basic emotions, namely happiness, sadness, anger, and a neutral state. The visualization of these four emotional expressions is shown in Figure 2.

Two pilot usability tests took place. The first test aimed to find out which eye shapes fit the different emotions. An application based on human emotional perception was made in Processing language for the testing. The application randomly generated eyes that exhibited the specified four emotions and different levels of expression of these emotions. We tested with several fellow students and the results were exported to a table, providing us with a lookup table for each of the required facial expressions (see Figure 3), which we later used to train the learning algorithm. The blank ones were not associated with any of the emotions and were not used for training or as a valid expressions.

The second test needed to establish the connection between the expressed emotions by a person and the response of the drone, i.e. the affective interaction. Although the concept is created for a drone, a prototype for testing has been developed on a computer screen. For this test, the human will be in front of a laptop equipped with a webcam. The persons's face is analysed in order to determine its facial expression. The computer screen shows the corresponding eyes of the drone and is placed on a comfortable distance in front of the person.

Intelligent behavior and embodiment

Current human-computer interaction (HCI) designs generally involve traditional interface devices such as the keyboard and mouse and are constructed to emphasize the transmission of explicit

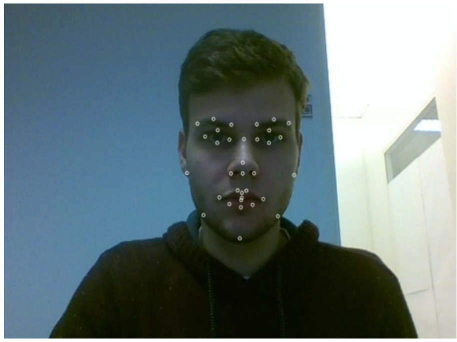

Figure 4: Facial emotion tracking by Affectiva SDK.

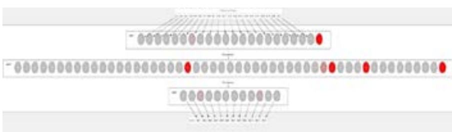

Figure 5: The used neural architecture in Neuroph studio.

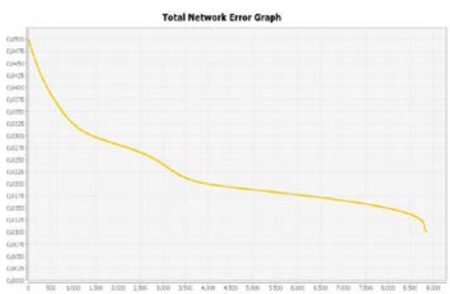

Figure 6: Graph displaying the decline of the learning error.

messages while ignoring implicit information about the user, such as changes in the affective state [12].

On the level of physiology, the sympathetic nervous system prepares the body for action and indicates the change of emotional state: increased blood pressure and heart rate, respiration increases, and pupil dilation. On a behavioral level, emotions are expressed using body posture, facial expressions approach/avoidance, and different accelerations of movement [4]. Plenty of methods to detect human emotion using audio or visual cues have been developed. In public spaces, audio information is too difficult to process due to the noise. In public areas, few people use body gesture to express emotion. Therefore for our context, the facial expression is the most straightforward and easiest method of emotional expression to detect.

Design of Neural-based controller for human-drone emotional interaction

We used the Affectiva SDK for facial emotion detection and analysis of the expression obtained from the camera. The 21 expressions output (e.g., brow raise, cheek raise, jaw drop, etc.) are used as the inputs for a neural network, training the network to link it to certain emotional expressions (see Figure 4).

Training data. Training data was collected from 5 persons by tracking 21 different points in their face using Affectiva's SDK. The participants were asked to express four emotions: happiness, sadness, anger and a neutral expression on three intensity levels from low to high, providing 12 known outputs. Since the neutral emotion does not have different intensity levels, we asked participants to vary their neutral expression slightly.

Neural network. Using Neuroph Studio, a multilayer perceptron network is set up with 21 inputs, a hidden layer with 50 nodes and 12 outputs (see Figure 5). The network was trained in the Neuroph Studio using supervised learning to train the data. The learning parameters are set to have a 0.01 max error and a learning rate of 0.2. The network was trained until the error rate decreased to 0.01 as can be seen in Figure 6. The network is exported to a *.nnet file which is imported into Processing to create an online interactive prototype.

Relationship building

To develop a realistic interaction between a human and a drone, the drone should be able to recognize individual human faces and react based on their previous mutual experiences. As shown in [12], people seem to have emotional memory – previous encounters influence their current emotion. A simplified version of such a relationship was implemented in the current system, utilizing previous facial expressions from the user to determine the state of their relationship. Happy or angry gazes from the user either positively or negatively affect this state.

Although the process of building a relationship is overly simplified in this initial phase of testing, the people will notice that the drone will not just mimic them. In the current experiment, the participant will see the relationship level on the screen as a numerical value, in order to make the person more aware of the context of the drone behavior. This level is a number where low means the relationship is mostly negative and high means that it is positive. When the relationship is good, the drone will react more happy and compassionate, whereas in a bad relationship the drone will have a more angry expression. Furthermore, the participant will eventually notice that positive facial expressions will make the relationship value go up, and see it decline when looking angry.

Table 1: Comparison of the emotion estimation of our network and Affectiva, a validated software for emotion estimation.

Emotion	Our network	Affectiva
Happy 1	Happy 2	Joy: 90-100%
Happy 2	Happy 2	Joy: 100%
Happy 3	Happy 3	Joy: 100%
Sad 1	Sad 1	Neutral
Sad 2	Sad 2	Sad: 0-2%
Sad 3	Sad 1	Sad: 20-40%
Angry 1	Neutral	Anger: 10-20%
Angry 2	Angry 2	Anger: 20-30%
Angry 3	Angry 2	Anger: 35-40%
Neutral	Neutral	Neutral

TESTING AND ANALYSIS

As previously mentioned, the Affectiva SDK was used to gather live data. This SDK features emotion detection as well based on its deep learning algorithm. The Affectiva emotion detection was needed for developing our system to compare the emotion estimation made by Affectiva with the results from our learning algorithm. We needed to implement own learning algorithm, so the pattern classification can be embedded in a flying drone with limited computational capacity.

For an illustration, different facial expressions were analyzed by the two systems, providing both with three different emotion levels for happy, angry, sad and neutral and comparing the results. The output from Affectiva is measured in percentages. The test subject had not been included in the training set for either of the two systems.

The presented neural network showed to be quite accurate in detecting the expressed emotion. However, the intensity of the recognized emotion was sometimes classified in the neighboring class – a bit angry as neutral, etc. (see Table 1).

DISCUSSION

We designed a system for emotional interaction of a social drone aiming to build longitudinal empatic relationships. The drone uses a neural learning for emotion recognition and heuristics for relationship building to produce an emotional expression using the drone eyes. This work is in a preliminary phase – a lot of additional work is needed to determine the proper data-driven model for relationship building in design through research approach. The prototype is working and ready for implementation on the BlueJay drone, which is a research platform for domestic and indoor drones that takes place at the Eindhoven University of Technology.

Currently, the tests are performed with a screen version of the eyes, rather than using eyes on an actual drone. The emotion recognition system utilizes a stationary setup as well. After implementation on the drone itself, some real-life constraints may arise.

The learning algorithm can recognize three intensities of four different emotions. The number of emotions could be expanded to create more complex interactions between drones and humans. It should be mentioned that although the data from the test subject had not been used to train the neural network, the training and testing took place in a similar setup as the training data gathering. While happiness is rather easy to express, the facial expressions for sadness and anger may not fully resemble natural facial expressions during those emotions, as the training set for these emotions was created while acting.

The relationship level is currently rapidly changing from positive to negative. For demonstration purposes, these values are close together and change based on the emotion displayed from the user. The current prototype proposes a very simple application of relationship building between human and drone. Gazing angrily at the drone will negatively impact the relationship between human and drone and produce an unfriendly facial expression from the drone in return. Changing the facial expression of the human to a friendlier one will not directly result in a friendly response, although it will improve the relationship. Looking angrily at the drone in a positive relationship will produce a sad expression from the drone and negatively impact the relationship. Since human relationships are far more complex, future studies could find correlations based on emotions and relationships. The ongoing research on this subject such as in [10][12] should be used to improve this interaction.

A large training set is needed for better generalization of the algorithm. Currently, we are unaware of how well our algorithm recognizes people from different ages and ethnicities, although within the training set already a diversity of male & female, and Asian & Caucasian participants are present.

REFERENCES

[1] [n. d.]. Drone Mapping Software for Desktop + Cloud + Mobile. Retrieved January 27, 2017 from https://pix4d.com/.

[2] [n. d.]. Unmanned Aircraft Systems - Aerialtronics. Retrieved January 27, 2017 from www.aerialtronics.com/ search-rescue-sar/.

[3] Anas, SAB,Qiu, S., Rauterberg, M., & Hu, J. (2016, October). Exploring Social Interaction with Everyday Object based on Perceptual Crossing. In *Proceedings of the Fourth International Conference on Human Agent Interaction* (pp. 11-18). ACM.

[4] Barakova, E. I., & Lourens, T. (2010). Expressing and interpreting emotional movements in social games with robots. *Personal and ubiquitous computing*, *14*(5), 457-467

[5] Cynthia Breazeal. 2003. Emotion and sociable humanoid robots. *International Journal of Human-Computer Studies* 59, 1-2 (2003), 119–155.

[6] Paul Ekman and Harriet Oster. 1979. Facial expressions of emotion. *Annual review of psychology* 30, 1 (1979), 527–554.

[7] Carl Benedikt Frey and Michael A Osborne. 2017. The future of employment: how susceptible are jobs to computerisation? *Technological forecasting and social change* 114 (2017), 254–280.

[8] Alison George. 2013. Forget roads, drones are the future of goods transport. *New Scientist* 219, 2933 (2013), 27.

[9] Barakova, E. I., Gorbunov, R., & Rauterberg, M. (2015). Automatic interpretation of affective facial expressions in the context of interpersonal interaction. *IEEE transactions on human-machine systems*, *45*(4), 409-418.

[10] Gorbunov, R., Barakova, E. I., & Rauterberg, M. (2017, June). Memory effect in expressed emotions during long term group interactions. In International Work-Conference on the Interplay Between Natural and Artificial Computation (pp. 254-264).

[11] Lowe, R., Barakova, E., Billing, E., & Broekens, J. (2016). Grounding emotions in robots, *Adaptive Behavior, Vol 24(5)* 263-266.

[12] Jawad Nagi, Alessandro Giusti, Gianni A Di Caro, and Luca M Gambardella. 2014. Human control of UAVs using face pose estimates and hand gestures. In *Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction*. ACM, 252–253.

[13] Wai Shan Ng and Ehud Sharlin. 2011. Collocated interaction with flying robots. In *RO-MAN, 2011 IEEE*. IEEE, 143–149.

[14] Panagiotis Papadakis, Patrick Rives, and Anne Spalanzani. 2014. Adaptive spacing in human-robot interactions. In *Intelligent Robots and Systems (IROS 2014), 2014 IEEE/RSJ International Conference on*. IEEE, 2627–2632.

[15] Kwang-Hyun Park, Hyong-Euk Lee, Youngmin Kim, and Z Zenn Bien. 2008. A steward robot for human-friendly human-machine interaction in a smart house environment. *IEEE Transactions on Automation Science and Engineering* 5, 1 (2008), 21–25.

[16] Daniel Szafir, Bilge Mutlu, and Terry Fong. 2015. Communicating directionality in flying robots. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*. ACM, 19–26.

[17] Nhu Khue Vuong, Syin Chan, and Chiew Tong Lau. 2015. mHealth sensors, techniques, and applications for managing wandering behavior of people with dementia: A review. In *Mobile Health*. Springer, 11–42.

[18] Zwaan, S. G., & Barakova, E. I. (2016, June). Boxing against drones: Drones in sports education. In *Proceedings of the The 15th International Conference on Interaction Design and Children* (pp. 607-612). ACM.